

HW4-STAT2131

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Question1

```
library(ggplot2)
Cosme_data <- read.csv("CosmeticsSales.txt",header = TRUE,sep=" ", col.names = c("Y","X1","X2","X3"))
head(Cosme_data)
```

```
##      Y  X1  X2  X3
## 1 12.85 5.6 5.6 3.8
## 2 11.55 4.1 4.8 4.8
## 3 12.78 3.7 3.5 3.6
## 4 11.19 4.8 4.5 5.2
## 5  9.00 3.4 3.7 2.9
## 6  9.34 6.1 5.8 3.4
```

Part1:

```
model_cosme1 <- lm(Y~X1, data = Cosme_data)
summary(model_cosme1)
```

```
##
## Call:
## lm(formula = Y ~ X1, data = Cosme_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.0060 -0.7919  0.1584  1.2961  3.4824
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.1628     0.6712   4.712 2.69e-05 ***
## X1            1.6581     0.1641  10.104 8.23e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.892 on 42 degrees of freedom
## Multiple R-squared:  0.7085, Adjusted R-squared:  0.7016
## F-statistic: 102.1 on 1 and 42 DF,  p-value: 8.231e-13
```

Part2:

```
model_cosme2 <- lm(Y~X2,data = Cosme_data)
summary(model_cosme2)
```

```
##
## Call:
## lm(formula = Y ~ X2, data = Cosme_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.4287 -1.2874  0.2027  1.0759  3.6742
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.8315     0.6990   4.051 0.000215 ***
## X2            1.7926     0.1769  10.135 7.51e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.888 on 42 degrees of freedom
## Multiple R-squared:  0.7098, Adjusted R-squared:  0.7029
## F-statistic: 102.7 on 1 and 42 DF,  p-value: 7.507e-13
```

Part3:

```
Full_model_cosm <- lm(Y~X1+X2+X3, data = Cosme_data)
summary(Full_model_cosm)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X2 + X3, data = Cosme_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.4217 -0.9115  0.0703  1.1420  3.5479
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.0233     1.2029   0.851  0.4000
## X1            0.9657     0.7092   1.362  0.1809
## X2            0.6292     0.7783   0.808  0.4237
## X3            0.6760     0.3557   1.900  0.0646 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.825 on 40 degrees of freedom
## Multiple R-squared:  0.7417, Adjusted R-squared:  0.7223
## F-statistic: 38.28 on 3 and 40 DF,  p-value: 7.821e-12
```

```
model_cosmex1x3 <- lm(Y ~ X1 +X3, data = Cosme_data)
summary(model_cosmex1x3)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X3, data = Cosme_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.5934 -1.0162  0.1808  1.1548  3.4955
```

```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.0173     1.1978   0.849   0.4006
## X1             1.5221     0.1701  8.948 3.45e-11 ***
## X3             0.7362     0.3464   2.125   0.0396 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.818 on 41 degrees of freedom
## Multiple R-squared:  0.7374, Adjusted R-squared:  0.7246
## F-statistic: 57.58 on 2 and 41 DF,  p-value: 1.242e-12

model_cosmex2x3 <- lm(Y~X2+X3,data = Cosme_data)
summary(model_cosmex2x3)
```

```
##
## Call:
## lm(formula = Y ~ X2 + X3, data = Cosme_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.1265 -0.9973  0.0202  0.9655  3.6581
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.0861     1.2144   0.894   0.3764
## X2             1.6577     0.1894  8.752 6.31e-11 ***
## X3             0.6205     0.3571   1.738   0.0897 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.844 on 41 degrees of freedom
## Multiple R-squared:  0.7297, Adjusted R-squared:  0.7165
## F-statistic: 55.34 on 2 and 41 DF,  p-value: 2.255e-12
```

Comment: For the simple linear model $Y \sim X1$ and $Y \sim X2$, we can see $X1$ and $X2$ both statistically influence Y , $p\text{-value} < 0.05$; For the marginal t-test of $X1$ and $X2$ with controlling $X3$, say like $Y \sim X1 + X3$ and $Y \sim X2 + X3$, we can see $X1$ and $X2$ also statistically influence Y , $p\text{-value} < 0.05$. But for the full model $Y \sim X1 + X2 + X3$, both $X1$ and $X2$ do not statistically influence Y , the $p\text{-values}$ are even far larger than 0.1. That might because there exist Multicollinearity among variables, in this case, $X1$ and $X2$ may have linear relationship.

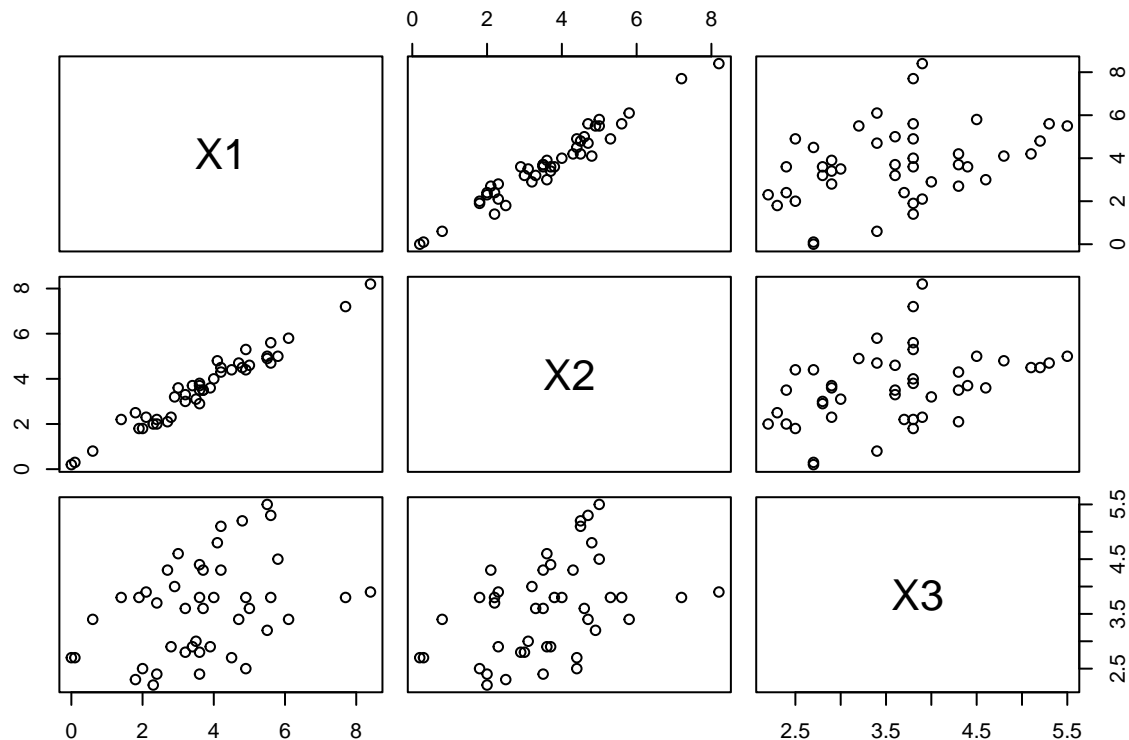
Part4:

```
library(car)

## Loading required package: carData
vif(Full_model_cosm)

##           X1           X2           X3
## 20.072031 20.716101  1.217973

pairs(~X1+X2+X3, data=Cosme_data)
```



We can see from the output of VIF and pairs plot, VIF values of X1 and X2 is far larger than 10, which means they have strong Multicollinearity. VIF value of X3 means X3 does not have multicollinearity with any other variables. The pair plot shows obviously X1 and X2 has linear relationship.

Problem2:

```
credit_data <- read.csv("Credit.csv",header = TRUE, sep=",")
head(credit_data)
```

```
##   X  Income Limit Rating Cards Age Education Gender Student Married Ethnicity
## 1 1  14.891  3606   283    2  34         11  Male      No      Yes Caucasian
## 2 2 106.025  6645   483    3  82         15 Female    Yes      Yes    Asian
## 3 3 104.593  7075   514    4  71         11  Male      No      No    Asian
## 4 4 148.924  9504   681    3  36         11 Female    No      No    Asian
## 5 5  55.882  4897   357    2  68         16  Male      No      Yes Caucasian
## 6 6  80.180  8047   569    4  77         10  Male      No      No    Caucasian
```

```
##   Balance
```

```
## 1    333
## 2    903
## 3    580
## 4    964
## 5    331
## 6   1151
```

```
library(leaps)
```

```
best_subset_credit <- regsubsets(Balance~Income+Limit+Rating+Cards+Age+Education+Gender+Student+Married+
summary(best_subset_credit)
```

```
## Subset selection object
```

```
## Call: regsubsets.formula(Balance ~ Income + Limit + Rating + Cards +
```

```
##   Age + Education + Gender + Student + Married + Ethnicity,
```

```
##   data = credit_data)
```

```

## 11 Variables (and intercept)
##               Forced in Forced out
## Income                FALSE      FALSE
## Limit                  FALSE      FALSE
## Rating                  FALSE      FALSE
## Cards                   FALSE      FALSE
## Age                     FALSE      FALSE
## Education               FALSE      FALSE
## GenderFemale            FALSE      FALSE
## StudentYes              FALSE      FALSE
## MarriedYes              FALSE      FALSE
## EthnicityAsian          FALSE      FALSE
## EthnicityCaucasian      FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##               Income Limit Rating Cards Age Education GenderFemale StudentYes
## 1 ( 1 ) " "      " "      "*"    " "    " " " "      " "      " "
## 2 ( 1 ) "*"      " "      "*"    " "    " " " "      " "      " "
## 3 ( 1 ) "*"      " "      "*"    " "    " " " "      " "      "*"
## 4 ( 1 ) "*"      "*"    " "      "*"    " " " "      " "      "*"
## 5 ( 1 ) "*"      "*"    "*"    "*"    " " " "      " "      "*"
## 6 ( 1 ) "*"      "*"    "*"    "*"    "*" " "      " "      "*"
## 7 ( 1 ) "*"      "*"    "*"    "*"    "*" " "      "*"      "*"
## 8 ( 1 ) "*"      "*"    "*"    "*"    "*" " "      "*"      "*"
##               MarriedYes EthnicityAsian EthnicityCaucasian
## 1 ( 1 ) " "      " "      " "
## 2 ( 1 ) " "      " "      " "
## 3 ( 1 ) " "      " "      " "
## 4 ( 1 ) " "      " "      " "
## 5 ( 1 ) " "      " "      " "
## 6 ( 1 ) " "      " "      " "
## 7 ( 1 ) " "      " "      " "
## 8 ( 1 ) " "      "*"      " "

best_sse <- summary(best_subset_credit)
sse <- best_sse$rss
sse

## [1] 21435122 10532541 4227219 3915058 3866091 3821620 3810759 3804746

forward_credit <- regsubsets(Balance~Income+Limit+Rating+Cards+Age+Education+Gender+Student+Married+Ethnicity,
summary(forward_credit)

## Subset selection object
## Call: regsubsets.formula(Balance ~ Income + Limit + Rating + Cards +
##      Age + Education + Gender + Student + Married + Ethnicity,
##      data = credit_data, nbest = 1, method = "forward")
## 11 Variables (and intercept)
##               Forced in Forced out
## Income                FALSE      FALSE
## Limit                  FALSE      FALSE
## Rating                  FALSE      FALSE
## Cards                   FALSE      FALSE
## Age                     FALSE      FALSE
## Education               FALSE      FALSE
## GenderFemale            FALSE      FALSE

```

```

## StudentYes          FALSE      FALSE
## MarriedYes          FALSE      FALSE
## EthnicityAsian      FALSE      FALSE
## EthnicityCaucasian  FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: forward
##      Income Limit Rating Cards Age Education GenderFemale StudentYes
## 1 ( 1 ) " "      " "      "*"      " "      " " " "      " "      " "
## 2 ( 1 ) "*"      " "      "*"      " "      " " " "      " "      " "
## 3 ( 1 ) "*"      " "      "*"      " "      " " " "      " "      "*"
## 4 ( 1 ) "*"      "*"      "*"      " "      " " " "      " "      "*"
## 5 ( 1 ) "*"      "*"      "*"      "*"      " " " "      " "      "*"
## 6 ( 1 ) "*"      "*"      "*"      "*"      "*"      " "      " "      "*"
## 7 ( 1 ) "*"      "*"      "*"      "*"      "*"      " "      "*"      "*"
## 8 ( 1 ) "*"      "*"      "*"      "*"      "*"      " "      "*"      "*"
##      MarriedYes EthnicityAsian EthnicityCaucasian
## 1 ( 1 ) " "      " "      " "
## 2 ( 1 ) " "      " "      " "
## 3 ( 1 ) " "      " "      " "
## 4 ( 1 ) " "      " "      " "
## 5 ( 1 ) " "      " "      " "
## 6 ( 1 ) " "      " "      " "
## 7 ( 1 ) " "      " "      " "
## 8 ( 1 ) " "      "*"      " "

forward_sse <- summary(forward_credit)$rss
forward_sse

## [1] 21435122 10532541 4227219 4032502 3866091 3821620 3810759 3804746

backward_credit <- regsubsets(Balance~Income+Limit+Rating+Cards+Age+Education+Gender+Student+Married+Ethnicity,
summary(backward_credit))

## Subset selection object
## Call: regsubsets.formula(Balance ~ Income + Limit + Rating + Cards +
##      Age + Education + Gender + Student + Married + Ethnicity,
##      data = credit_data, nbest = 1, method = "backward")
## 11 Variables (and intercept)
##      Forced in Forced out
## Income          FALSE      FALSE
## Limit           FALSE      FALSE
## Rating          FALSE      FALSE
## Cards           FALSE      FALSE
## Age            FALSE      FALSE
## Education       FALSE      FALSE
## GenderFemale    FALSE      FALSE
## StudentYes      FALSE      FALSE
## MarriedYes      FALSE      FALSE
## EthnicityAsian  FALSE      FALSE
## EthnicityCaucasian FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: backward
##      Income Limit Rating Cards Age Education GenderFemale StudentYes
## 1 ( 1 ) " "      "*"      " "      " "      " " " "      " "      " "
## 2 ( 1 ) "*"      "*"      " "      " "      " " " "      " "      " "

```

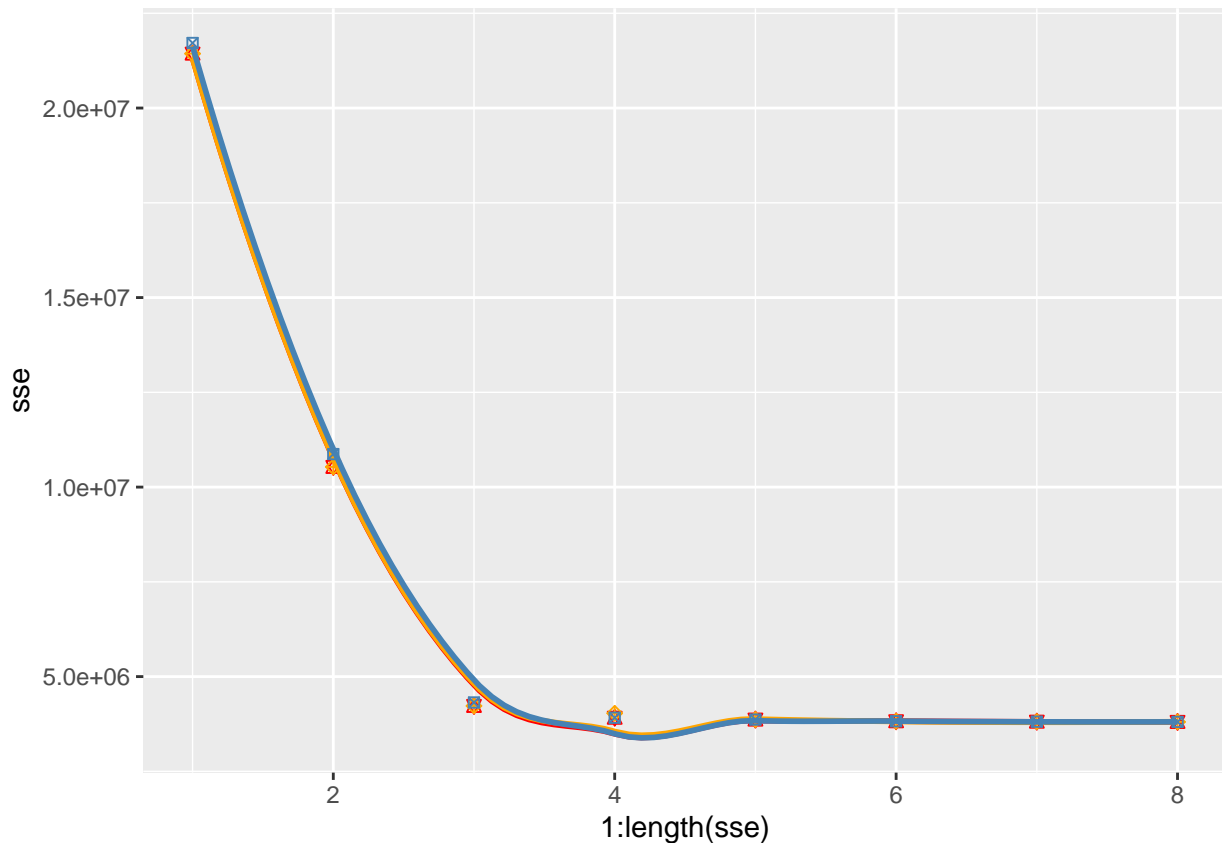
```
## 3 ( 1 ) "*"      "*"      " "      " "      " "      " "      " "      "*"
## 4 ( 1 ) "*"      "*"      " "      "*"      " "      " "      " "      "*"
## 5 ( 1 ) "*"      "*"      "*"      "*"      " "      " "      " "      "*"
## 6 ( 1 ) "*"      "*"      "*"      "*"      "*"      " "      " "      "*"
## 7 ( 1 ) "*"      "*"      "*"      "*"      "*"      " "      "*"      "*"
## 8 ( 1 ) "*"      "*"      "*"      "*"      "*"      " "      "*"      "*"
##      MarriedYes EthnicityAsian EthnicityCaucasian
## 1 ( 1 ) " "      " "      " "
## 2 ( 1 ) " "      " "      " "
## 3 ( 1 ) " "      " "      " "
## 4 ( 1 ) " "      " "      " "
## 5 ( 1 ) " "      " "      " "
## 6 ( 1 ) " "      " "      " "
## 7 ( 1 ) " "      " "      " "
## 8 ( 1 ) " "      "*"      " "
```

```
backward_sse <- summary(backward_credit)$rss
backward_sse
```

```
## [1] 21715657 10870832 4316997 3915058 3866091 3821620 3810759 3804746
```

```
ggplot() +
  geom_point(data = data.frame(sse), aes(x=1:length(sse),y=sse), shape=11, color="red")+
  geom_smooth(data = data.frame(sse), aes(x=1:length(sse),y=sse),se=FALSE,color="red")+
  geom_point(data = data.frame(forward_sse), aes(x=1:length(sse),y=forward_sse),shape=9, color="orange")+
  geom_smooth(data = data.frame(forward_sse), aes(x=1:length(sse),y=forward_sse),se=FALSE,color="orange")+
  geom_point(data = data.frame(backward_sse), aes(x=1:length(sse),y=backward_sse),shape=7, color="steelblue")+
  geom_smooth(data = data.frame(backward_sse), aes(x=1:length(sse),y=backward_sse),se=FALSE,color="steelblue")
```

```
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



Part2:

```
best_subsect_Cp <- summary(best_subset_credit)$cp
best_subsect_bic <- summary(best_subset_credit)$bic
best_subsect_Cp;
```

```
## [1] 1800.308406 685.196514 41.133867 11.148910 8.131573 5.574883
## [7] 6.462042 7.845931
```

```
best_subsect_bic;
```

```
## [1] -535.9468 -814.1798 -1173.3585 -1198.0527 -1197.0957 -1195.7321 -1190.8790
## [8] -1185.5192
```

```
optimal_best_subsect_Cp <- which.min(best_subsect_Cp)
optimal_best_subsect_bic <- which.min(best_subsect_bic)
print(summary(best_subset_credit)$which[optimal_best_subsect_Cp, ])
```

```
##      (Intercept)      Income      Limit      Rating
##           TRUE           TRUE           TRUE           TRUE
##      Cards      Age      Education      GenderFemale
##           TRUE           TRUE           FALSE           FALSE
##      StudentYes      MarriedYes      EthnicityAsian      EthnicityCaucasian
##           TRUE           FALSE           FALSE           FALSE
```

```
print(summary(best_subset_credit)$which[optimal_best_subsect_bic, ])
```

```
##      (Intercept)      Income      Limit      Rating
##           TRUE           TRUE           TRUE           FALSE
```



```
##          Cards          Age          Education          GenderFemale
##          TRUE          FALSE          FALSE          FALSE
##    StudentYes    MarriedYes    EthnicityAsian    EthnicityCaucasian
##          TRUE          FALSE          FALSE          FALSE
```

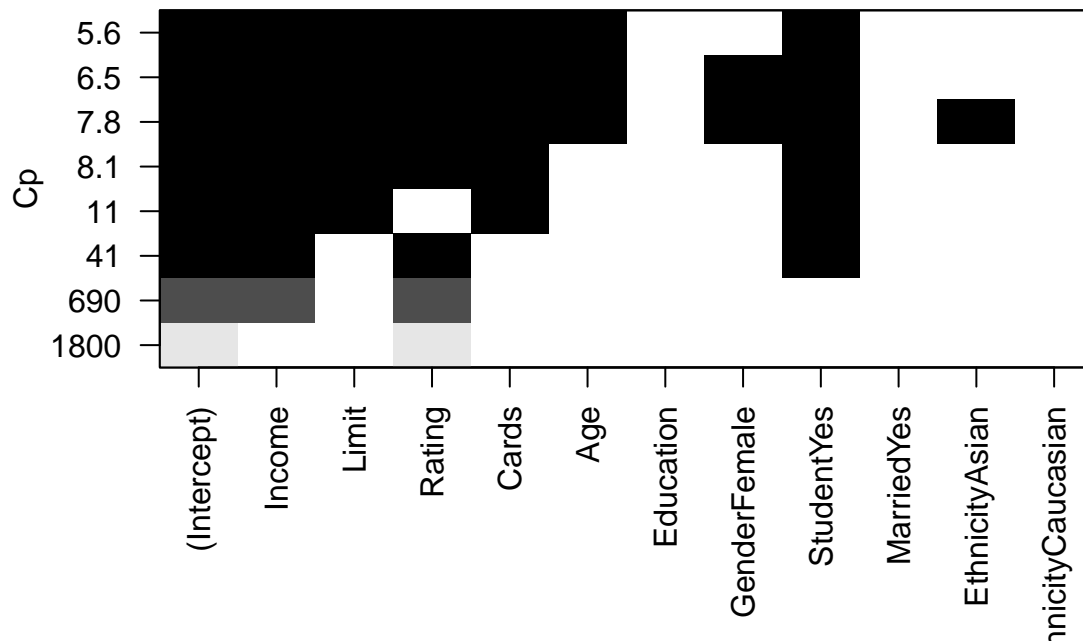
```
optimal_best_subset_Cp;
```

```
## [1] 6
```

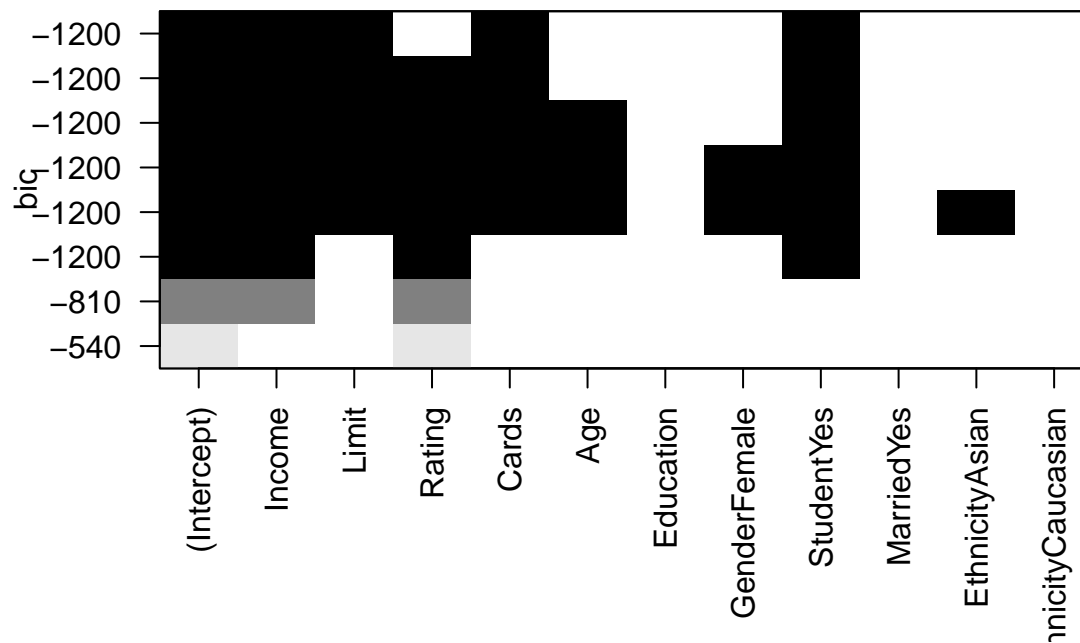
```
optimal_best_subset_bic
```

```
## [1] 4
```

```
plot(best_subset_credit, scale = "Cp")
```



```
plot(best_subset_credit, scale = "bic")
```



```
forward_Cp <- summary(forward_credit)$cp
forward_bic <- summary(forward_credit)$bic
forward_Cp;
```

```
## [1] 1800.308406 685.196514 41.133867 23.182500 8.131573 5.574883
## [7] 6.462042 7.845931
```

```
forward_bic;
```

```
## [1] -535.9468 -814.1798 -1173.3585 -1186.2300 -1197.0957 -1195.7321 -1190.8790
## [8] -1185.5192
```

```
optimal_forward_Cp <- which.min(forward_Cp)
optimal_forward_bic <- which.min(forward_bic)
print(summary(forward_credit)$which[optimal_forward_Cp, ])
```

```
##      (Intercept)      Income      Limit      Rating
##           TRUE           TRUE           TRUE           TRUE
##      Cards      Age      Education      GenderFemale
##           TRUE           TRUE           FALSE           FALSE
##      StudentYes      MarriedYes      EthnicityAsian      EthnicityCaucasian
##           TRUE           FALSE           FALSE           FALSE
```

```
print(summary(forward_credit)$which[optimal_forward_bic, ])
```

```
##      (Intercept)      Income      Limit      Rating
##           TRUE           TRUE           TRUE           TRUE
##      Cards      Age      Education      GenderFemale
##           TRUE           FALSE           FALSE           FALSE
##      StudentYes      MarriedYes      EthnicityAsian      EthnicityCaucasian
##           TRUE           FALSE           FALSE           FALSE
```

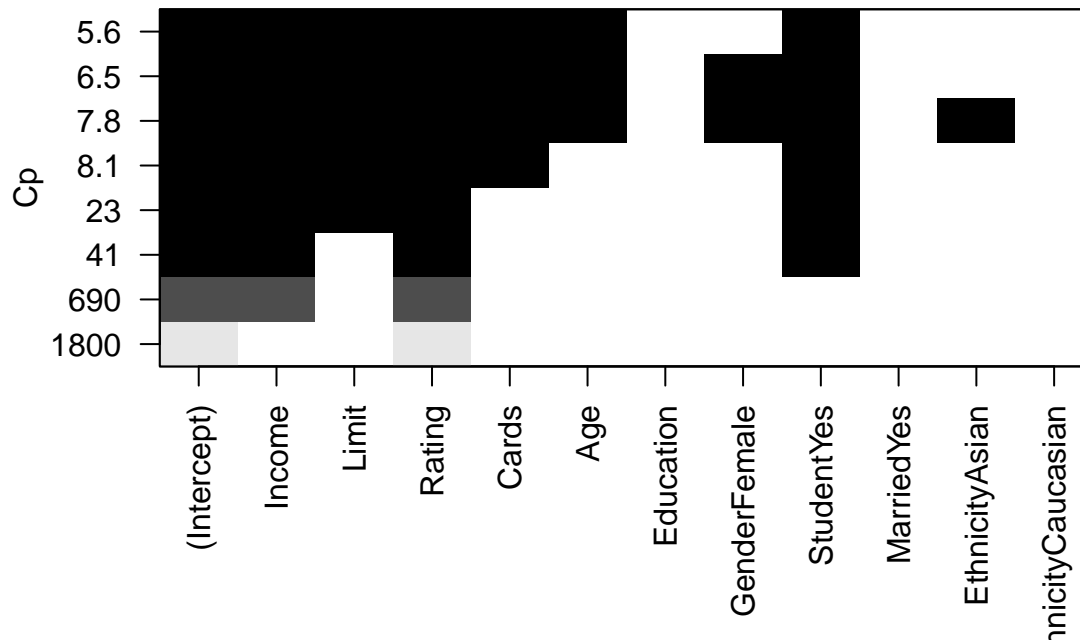
```
optimal_forward_Cp;
```

```
## [1] 6
```

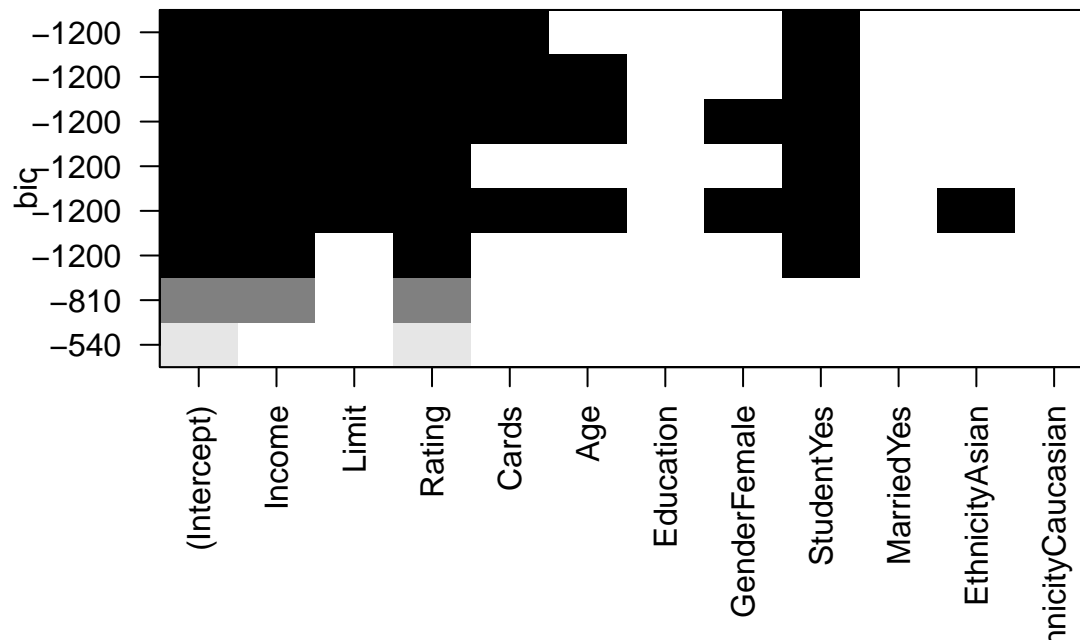
```
optimal_forward_bic
```

```
## [1] 5
```

```
plot(forward_credit, scale = "Cp")
```



```
plot(forward_credit, scale = "bic")
```



```
backward_Cp <- summary(backward_credit)$cp
backward_bic <- summary(backward_credit)$bic
backward_Cp;
```

```
## [1] 1829.052845 719.858831 50.332736 11.148910 8.131573 5.574883
## [7] 6.462042 7.845931
```

```
backward_bic;

## [1] -530.7458 -801.5344 -1164.9522 -1198.0527 -1197.0957 -1195.7321 -1190.8790
## [8] -1185.5192
```

```
optimal_backward_Cp <- which.min(backward_Cp)
optimal_backward_bic <- which.min(backward_bic)
print(summary(backward_credit)$which[optimal_backward_Cp, ])
```

```
##      (Intercept)      Income      Limit      Rating
##           TRUE           TRUE           TRUE           TRUE
##      Cards      Age      Education      GenderFemale
##           TRUE           TRUE           FALSE           FALSE
##      StudentYes      MarriedYes      EthnicityAsian      EthnicityCaucasian
##           TRUE           FALSE           FALSE           FALSE
```

```
print(summary(backward_credit)$which[optimal_backward_bic, ])
```

```
##      (Intercept)      Income      Limit      Rating
##           TRUE           TRUE           TRUE           FALSE
##      Cards      Age      Education      GenderFemale
##           TRUE           FALSE           FALSE           FALSE
##      StudentYes      MarriedYes      EthnicityAsian      EthnicityCaucasian
##           TRUE           FALSE           FALSE           FALSE
```

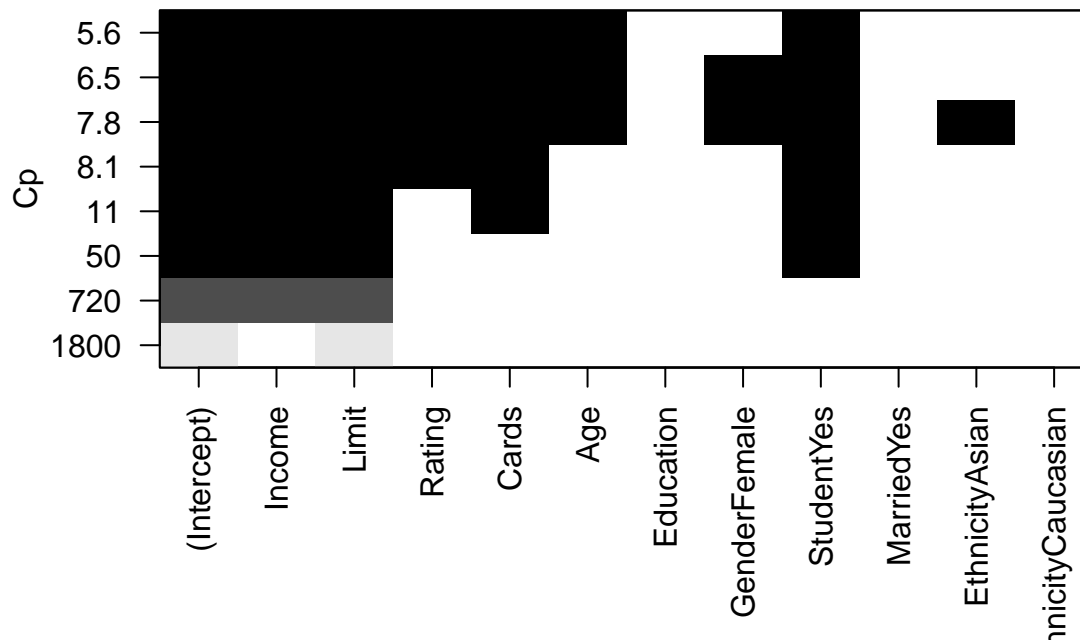
```
optimal_backward_Cp;
```

```
## [1] 6
```

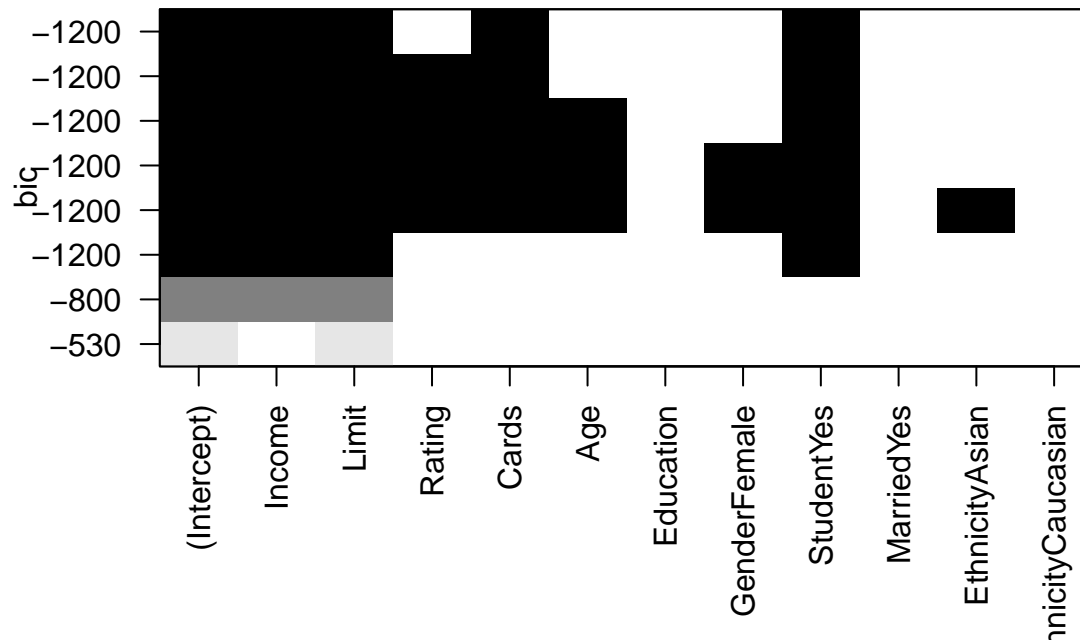
```
optimal_backward_bic
```

```
## [1] 4
```

```
plot(backward_credit, scale = "Cp")
```



```
plot(backward_credit, scale = "bic")
```



Now we have 3 subset select methods, for best subset procedure: optimal model is $\text{Balance} \sim \text{Income} + \text{Limit} + \text{Rating} + \text{Cards} + \text{Age} + \text{StudentYes}$, by using Cp and we have 6 predictors; optimal model is $\text{Balance} \sim \text{Income} + \text{Limit} + \text{Cards} + \text{StudentYes}$, by using BIC and we have 4 predictors.

For forward select: optimal model is $\text{Balance} \sim \text{Income} + \text{Limit} + \text{Rating} + \text{Cards} + \text{Age} + \text{StudentYes}$, by using Cp and we have 6 predictors; optimal model is $\text{Balance} \sim \text{Income} + \text{Limit} + \text{Rating} + \text{Cards} + \text{StudentYes}$, by using BIC and we have 5 predictors.

For backward select: optimal model is $\text{Balance} \sim \text{Income} + \text{Limit} + \text{Rating} + \text{Cards} + \text{Age} + \text{StudentYes}$, by using Cp and we have 6 predictors; optimal model is $\text{Balance} \sim \text{Income} + \text{Limit} + \text{Cards} + \text{StudentYes}$, by using BIC and we have 4 predictors.